Segmentation and Denoising of Noisy Satellite Images based on Modified Fuzzy C Means Clustering and Discrete Wavelet Transform for Information Retrieval

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***Abstract*— Image segmentation is one of the vital steps in satellite image processing for gathering information from the satellite images. Most of the satellite images suffer from noise and other disturbances. Sometimes noise pixels may be considered as image pixels resulting poor images. In this paper, to study the effectiveness of noise in the satellite images, different types of noises like Gaussian, poisson, salt & pepper and speckle noise are added to the original image. The discrete wavelet transform (DWT) and Bayes Shrink soft thresholding is then applied for the removal of noisy pixels and smoothen the image. In the final stage, the fuzzy based modified FCM clustering is performed on the denoised images to produce clusters or segmented result. This approach has been applied on the satellite images of various resolutions. The experimental results show that the proposed algorithm is efficient for providing robustness to noisy images.**

Keyword- Image Segmentation, Fuzzy-C-Means Clustering, Noise, Denoising, DWT, Threshoding

I. INTRODUCTION

The images received from satellite contains huge amount of data to decipher and process. But our human eye is insensitive to realize subtle changes in the image characteristics such as intensity, color, texture or brightness. So the manual human processing is not successful to retrieve the hidden treasures of information in the satellite image. The optimal solution is the processing of satellite images with digital computers. To retrieve the information or extract region of interest (ROI) from images, we need a segmentation method which is most important and difficult task in the image analysis. The segmentation is the process of grouping image pixels according to any one characteristics of the image. The goal of the segmentation process is to simplify and change the representation of an image into more meaningful and make easier to analyze[1,4,6,18]. Even though an intensity image has only 256 variations, a color satellite image may contain more number of colors. For example a RGB image may contain 256*256*256 colors. In this case, setting up crisp boundaries for color is impossible. So a fuzzy logic based approach, fuzzy-c-means algorithm, is the best solution for the segmentation of the satellite images to gather more information [8].

II. FUZZY BASED SEGMENTATION

Fuzzy Set Theory can be used in segmentation or clustering and it allows fuzzy boundaries to exist between different clustering. Each pixel of an image has a degree of membership to a region or a boundary. Even though there are a number of fuzzy approaches for image segmentation, one of the most widely used Fuzzy based approach for image segmentation called Fuzzy C Means (FCM) Clustering is used in this paper. FCM employs fuzzy partitioning such that a given data point can belong to several groups with the degree of belongingness specified by membership grades between 0 and 1. The FCM uses iterative procedure to calculate minimum of objective function. When the image segmentation is performed by FCM algorithm, image pixels are grouped into clusters and the grouped clusters are not with crisp boundaries [1]. This FCM algorithm returns values between 0 and 1.This is called Partition matrix which is used to write membership functions. These membership functions used for the purpose of reconstruct the segmented image.

A. Standard Fuzzy C Means Clustering Algorithm

The FCM clustering is the modified and fuzzified version of the hard c means or k-means clustering algorithm. Unlike k-means clustering, in the FCM clustering, data member i.e., image pixel can belong to more than one cluster. This iterative clustering procedure generates an optimal partition by minimizing the objective function given in (1).

$$J = \sum_{j=1}^{N} \sum_{i=1}^{c} U_{ij}^{m} \left\| X_j - V_i \right\|^2 \quad (1)$$

The FCM algorithm is based on minimizing its cost function or objective function. Consider a two dimensional satellite image f(x,y) which has N number of pixels (image elements). The objective is N partitioned into c number of clusters. $X = \{x_1, x_2, ..., x_n\}$ is the data set and c is the number of clusters with $2 \leq c \leq n$-1. The c centres can be represented by $V = \{v_1, v_2, ..., v_c\}$, V_i is the centre of the cluster i. The fuzzy partition matrix U_{ij} can be represented as $U_{ij} = U_i\ (X_j)$ is the degree of membership of X_j in the i^{th} cluster. The parameter m is used to determine the amount of fuzziness of the classification. In all cases m > 1.

$$U_{ij} = \sum_{k=1}^{c} \left\{ \frac{\|X_j - V_i\|}{\|X_j - V_k\|} \right\}^{-2/m-1} \quad (2)$$

$$V_i = \frac{\sum_{j=1}^{n} (U_{ij})^m X_j}{\sum_{j=1}^{n} (U_{ij})^m} \quad (3)$$

for i=1, 2…c and for j=1, 2…n

The standard FCM clustering algorithm is given below

1. Receive the image in the form of data matrix X
2. Fix the number of clusters, c ($2 \leq c \leq n$), n is the length of the image data
3. Assume the partition matrix, ***U***
4. Calculate the cluster centres,V_i, i = 1**… c** using (3)

5. Calculate the Euclidean distance matrix, ***D*** using following equation (4)

$$d_{ij} = \left\| X_j - V_i \right\| \quad (4)$$

6. Compute the cost or objective function according to Equation (5). Stop if either it is below a certain tolerance value or its improvement over previous iteration is below a certain threshold.

$$J(U, c_1, \dots, c_c) = \sum_{i=1}^{c} \sum_{j=1}^{n} u_{ij}^{m} d_{ij}^{2} \quad (5)$$

7. Compute a new **U** using Equation (6). Go to step 2

$$U_{ij} = \sum_{k=1}^{c} \left\{ \frac{\|X_j - V_i\|}{\|X_j - V_k\|} \right\}^{-2/m-1} \quad (6)$$

B. Modified FCM Clustering Algorithm

Even though FCM Clustering algorithm is very efficient and effective for satellite image segmentation, it has some drawbacks. Firstly, for clustering problems, the spatial information of data is important but the standard FCM doesn't give any spatial information. Secondly, when the noise pixels are incorporated with the image pixels, its memberships may be inaccurate and never correspond well to the degree of belonging of the data. So it is necessary to modify the standard FCM clustering algorithm. Here, the above mentioned drawbacks are taken into consideration and modified to incorporate the spatial information of image data. The spatial function can be defined as the weighted sum of the membership function in the neighbourhood of each pixel under consideration.

$$S_{ij} = \sum_{k \in W(X_j)} U_{ik} \alpha_{k1} + \frac{\sum_{k \epsilon (X_j)} U_{ik} \alpha_{k2}}{\sum_{t=1}^{c} \sum_{k \epsilon W(X_j)} U_{tk}} \quad (7)$$

where S_{ij} represents the probability that pixel X_j belongs to i^{th} clustering. $W(X_j)$ is a square window centred on pixel X_j in the spatial domain. To analyse whether the central pixel is classified exactly or not, it is necessary to compare the central pixel membership with the one of neighbour pixels in a window. The coefficient α_{k1} is used to remove or correct the misclassified pixels from the noisy regions. The coefficient α_{k2} quantitative the membership function according to the distance between pixels. After the spatial function is incorporated into the membership function, the new membership function as follows:

$$U_{ij(new)} = \frac{U_{ij}^{p} * S_{ij}^{q}}{\sum_{k=1}^{c} U_{kj}^{p} * S_{kj}^{q}} \quad (8)$$

for i=1,2,…..,c and j=1,2,……n and the parameters p and q are to control the relative importance of both spatial and membership function. When the noise pixel is incorporated with the image pixels, the misclassified pixels from noisy regions can easily be removed or corrected by using the equation (8). Every pixel in the image has a weight in relation to every cluster. So in noisy images, this weight W_{ji} is used to modify the fuzzy and typical partition and provides a better classification which is given as follows:

$$W_{ji} = \frac{1}{1+e^{-\left\{\frac{\|x_j - v_i\|^2}{\sum_{j=1}^{n}\|x_j - v_i\|^2 \left(\frac{c}{n}\right)}\right\}}} \tag{9}$$

The objective function of the modified FCM clustering algorithm can be formulated as follows:

$$J_{Mod} = \sum_{k=1}^{n}\sum_{i=1}^{c}\left(U_{ik}^{m}W_{ji}^{m}\right)\|X_k - V_i\|^2 \tag{10}$$

The Modified FCM clustering algorithm for satellite image segmentation is given below:

Step 1: Receive the image in the form of data matrix *X*

Step 2: Fix the number of clusters, c ($2 \le c \le n$), n is the length of the image data and m > 1

Step 3: Calculate the fuzzy partition matrix U_{ij} and, the i^{th} cluster centre V_i using (2) and (3)

Step 4: Calculate the spatial function S_{ij} and the weight function W_{ji} by using (7) and (9)

Step 5: Compute the new updated membership function using (8)

Step 6: Test for stopping condition. If not converged, go to step 4.

III. WAVELET TRANSFORM BASED IMAGE DENOISING

The wavelet is a set of orthonormal basis functions generated by dilation and translation operation of scaling function φ and a mother wavelet ψ. The wavelet basis or function can be localized in both frequency and space. This means the wavelet transform analyses the image information on both frequency and time scale. But the Fourier transform can be localized only in spatial domain. The wavelet basis is defined as

$$\psi(j,k)^{(x)} = 2^{\frac{j}{2}}\psi(2^{j}x - k) \tag{11}$$

The scaling function is defined as

$$\phi(j,k)^{(x)} = 2^{\frac{j}{2}}\phi(2^{j}x - k) \tag{12}$$

The denoising based on wavelets is performed by first decomposing the corrupt image into wavelet coefficients. Then, the wavelet coefficients are modified based on the soft or hard thresholding function. Finally, the inverse wavelet transform is performed on modified coefficients to obtain the reconstructed image. The basic procedure for wavelet based denoising is explained as

1. Apply discrete wavelet transform to the noisy Image. The wavelet transform decompose the image information into the wavelet coefficients.

2. Perform thresholding function to the wavelet coefficients components. Thresholding may be either soft or hard thresholding according to the application. The coefficients smaller than the threshold value is removed and the larger coefficients are retained

3. Apply the inverse discrete wavelet transform on the retained coefficients to obtain denoised estimate that is the reconstructed image.

The hard thresholding function is based on crisp logic which produces the result either 0 or 1. If the coefficients are larger than threshold, they are retained; otherwise, it is set to zero. The hard thresholding can be defined as

$$T_h = \begin{cases} x & for\ |x| \ge t \\ 0 & otherwise \end{cases} \tag{13}$$

In soft thresholding function the argument shrinks toward zero by the threshold. The soft-thresholding method yields more visually pleasant images over hard thresholding. The soft thresholding can be defined as

$$T_s = \begin{cases} sgn(x)(|x| - t) & for\ |x| \ge t \\ 0 & otherwise \end{cases} \tag{14}$$

Mallat [4] propose an algorithm for the efficient implementation of the wavelet transform. In this discrete wavelet coefficients calculated for a finite set of input data. This input data is applied to two convolution functions, each of which creates an output data that is half the length of the original input. First half of the output is produced by the low pass filter function and most of the information of the input signal (coarse coefficients) and the second half of the output is produced by the high pass filter function (detail coefficients). The low pass filter coefficients are used as the original signal for the next set of coefficients. This procedure is repeated recursively until a trivial number of low pass filter coefficients are left. The final output contains the remaining low pass filter outputs and the accumulated high pass filter outputs. This procedure is termed as decomposition. According to the inverse Mallat's algorithm, the quadrature mirror filters are applied with the coarse and detail coefficients. The outputs of the two filters are summed and are treated as the coarse coefficients for the next stage of reconstruction. This procedure is continued until the original data is obtained [10].

A. Wavelet Threshoding

There are number of methods for wavelet thresholding. Most widely used methods for image denoising include VisuShrink, Sure Shrink and BayesShrink [11,12]. The thresholding method VisuShrink was proposed by Donoho. In this threshold value t is proportional to the standard deviation of the noise. This hard thresholding method also known as universal threshold is defined as

$$T = \sigma\sqrt{2 \log n} \quad (15)$$

where *n* represents the signal size or number of samples, σ is the noise level and σ^2 is the noise variance present in the signal

1) *VisuShrink:* In VisuShrink a single value of threshold applied globally to all the wavelet coefficients. The main drawbacks of this method is (i) This method cannot be applied for minimizing the mean squared error (ii) removes too many coefficients (iii) It can only deal with an additive noise and cannot remove speckle noise
2) *Sure Shrink*: This soft thresholding proposed by Donoho and Johnstone. Since this method specifies a threshold value for each level of resolution (j) in the wavelet transform, also known as level dependent thresholding [11]. The objective of Sure Shrink is to minimize the mean squared error which is defined as

$$MSE = \frac{1}{n^2}\sum_{x,y=1}^{n}(n(x,y) - s(x,y))^2 \quad (16)$$

Where $s(x,y)$ is the original signal without noise, $z(x,y)$ is the estimate of the signal and *n* is the size of the signal. Sure Shrink removes noise by thresholding the empirical wavelet coefficients. This Sure Shrink threshold is defined as

$$T = \min\,(t, \sigma\sqrt{2 \log n}) \quad (17)$$

Where *t* is the value that minimizes Stein's Unbiased Risk Estimator, *n* is the size of the image and σ denotes the noise variance

3) *BayesShrink:* The thresholding method BayesShrink was proposed by Chang, Yu and Vetterli [11]. The objective of this method is to minimize the Bayesian risk. This approach follows soft thresholding rule and is sub band dependent. In this, thresholding is done at each band of resolution in the wavelet decomposition. In This case the threshold condition is defined as

$$T_b = \frac{\sigma^2}{\sigma_s} \quad (18)$$

where σ_s is the signal variance without noise and σ^2 is the noise variance.

IV. THE PROPOSED APPROACH FOR SEGMENTATION OF NOISY SATELLITE IMAGES

The Proposed method for segmentation of noisy satellite image is shown in Fig 1.The satellite images mostly contain noise and inhomogenity. Therefore an accurate segmentation of satellite images is very difficult task. However, the accurate segmentation of these images is very important and crucial for further image analysis processes [3]. The noise in the image is reduced using discrete wavelet transform. In this denoising process, the image is transformed into the wavelet coefficients and thresholding is applied to detail coefficients. The coefficients smaller than threshold value is eliminated. Then the inverse discrete wavelet transform is applied for approximations and detail coefficients. Finally, FCM Clusters input image into the 'n' number of clusters. The algorithm for the proposed approach is listed as follows

Step 1: Acquire the input satellite image

Step 2: Noise is applied to the input image

Step 3: Discrete Wavelet Transform (DWT) is applied to reduce the noise. The wavelet transform decompose the image information into the wavelet coefficients.

Step 4: Perform threshold function on the wavelet coefficients. In this paper, Bayes Shrink soft thresholding is used for the removal of the coefficients smaller than threshold value and the larger coefficients are retained

Step 5: Apply Inverse DWT for approximating the coefficients. In this step, IDWT is applied on the retained coefficients to obtain denoised estimate that is the reconstructed image.

Step 6: Apply modified FCM to segment the image

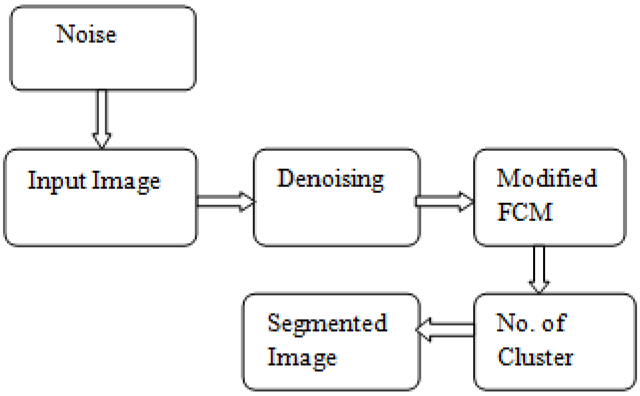


Fig 1. The Proposed System Architecture

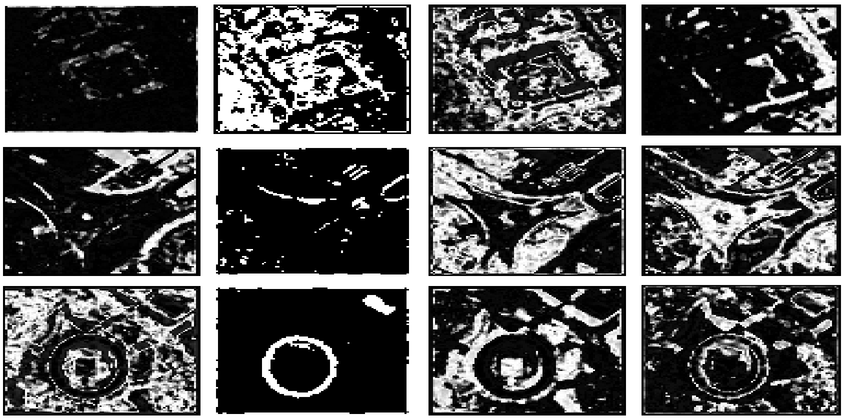
V. EXPERIMENTAL SETUP AND RESULT

For the simulation using Matlab, a data base of 25 satellite images was created to test the proposed modified FCM based approach for segmentation and denoising. This proposed algorithm was coded in Matlab 7.10 (R2010a) and executed using Intel core i3 system with 2GB RAM. Fig 2(a) shows the test RGB satellite images and its noisy version is shown in fig 2(b). Fig 2(c) and 2(d) represents the noisy gray scale image and denoised image respectively.

(a) (b) (c) (d)

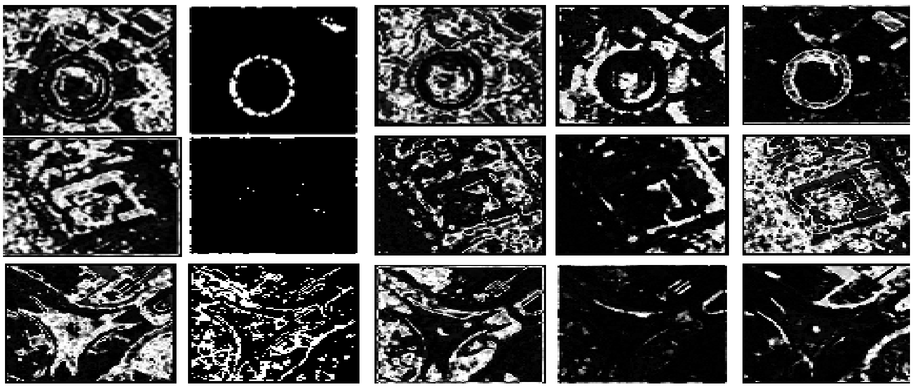
Fig 2. (a) Input image (b) input image with Gaussian noise (c) gray scale image with Gaussian noise (d) denoised image (Satellite image courtesy of GeoEye)

Fig 3 shows the segmentation result of the denoised image using the modified fuzzy c means clustering. We choose the number of cluster as four. Fig 4 shows the result for five clusters.



(a) (b) (c) (d)

Fig 3.The segmentation result for denoised images of 2(d) when the number of cluster is four
(a) cluster one (b) Cluster two (c) cluster three (d) cluster four



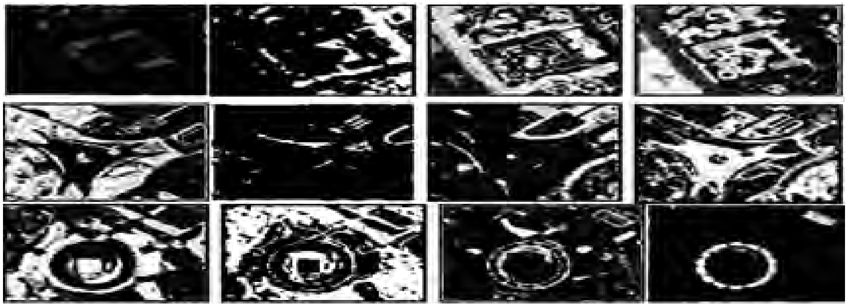
(a) (b) (c) (d) (e)

Fig 4.The segmentation result for denoised images of 2(d) when the number of cluster is five (a) cluster one
(b) Cluster two (c) cluster three (d) cluster four (e) cluster five

Fig 5(a) shows the test RGB satellite images and the same image with salt and pepper noise is shown in fig 5(b). Fig 5(c) and 5(d) represents the noisy gray scale image and denoised image respectively. Fig 6 shows the segmentation result of the denoised image using the modified fuzzy c means clustering. We choose the number of cluster as four. Fig 7 shows the result for five clusters.

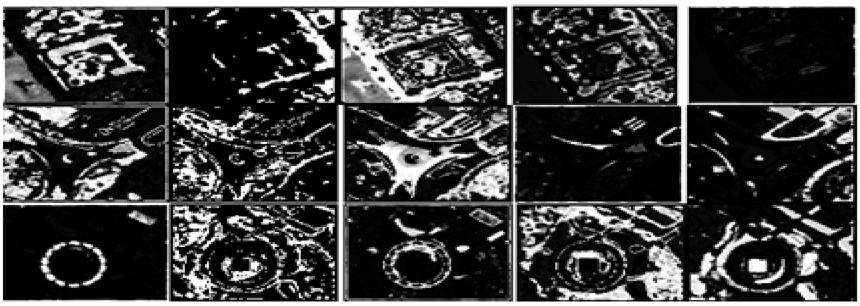
(a) (b) (c) (d)

Fig 5. (a) Input image (b) input image with salt and pepper noise (c) gray scale image with the noise
(d) denoised image



(a) (b) (c) (d)

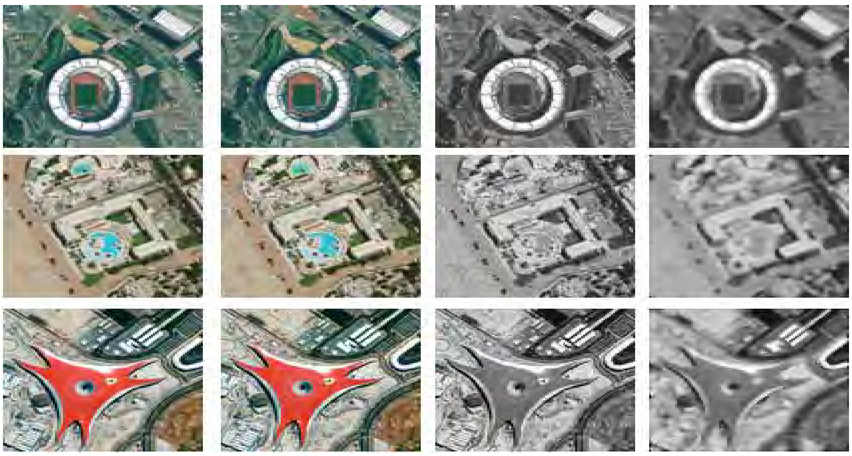
Fig 6.The segmentation result for denoised images of 5(d) when the number of cluster is four
(a) cluster one (b) cluster two (c) cluster three (d) cluster four



(a) (b) (c) (d) (e)

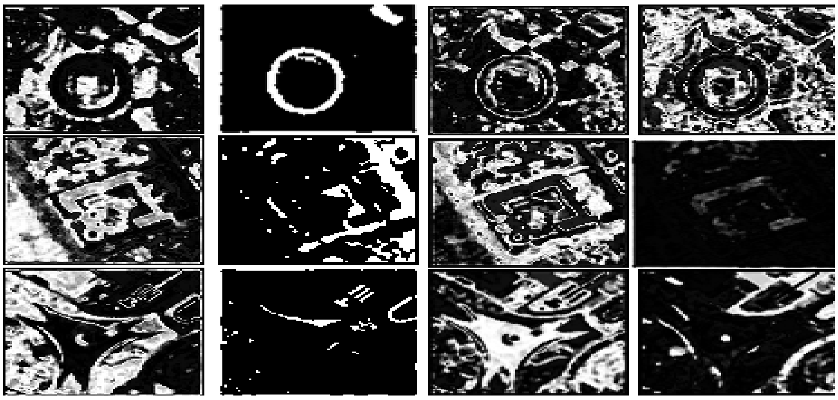
Fig 7.The segmentation result for denoised images of 5(d) when the number of cluster is five (a) cluster one
(b) Cluster two (c) cluster three (d) cluster four (e) cluster five

Fig 8(a) shows the test RGB satellite images and the same image with Poisson noise is shown in fig 8(b). Fig 8(c) and 8(d) represents the noisy gray scale image and denoised image respectively. Fig 9 shows the segmentation result of the denoised image using the modified fuzzy c means clustering. We choose the number of cluster as four. Fig 10 shows the result for five clusters. Fig 11, 12, and 13 shows the result for the speckle noise.



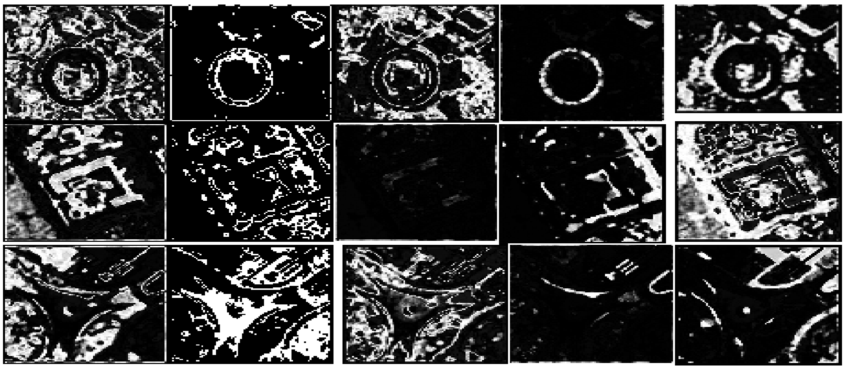
(a) (b) (c) (d)

Fig 8. (a) Input image (b) input image with Poisson noise (c) gray scale image with Poisson noise
(d) Denoised image



(a) (b) (c) (d)

Fig 9.The segmentation result for denoised images of 8(d) when the number of cluster is four
(a) Cluster one (b) Cluster two (c) cluster three (d) cluster four

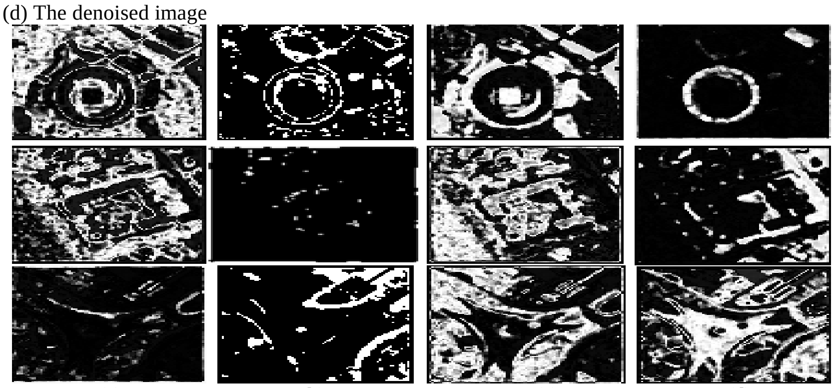


(a) (b) (c) (d) (e)

Fig 10.The segmentation result for denoised images of 8(d) when the number of cluster is five
(a) Cluster one (b) Cluster two (c) cluster three (d) cluster four (e) cluster five

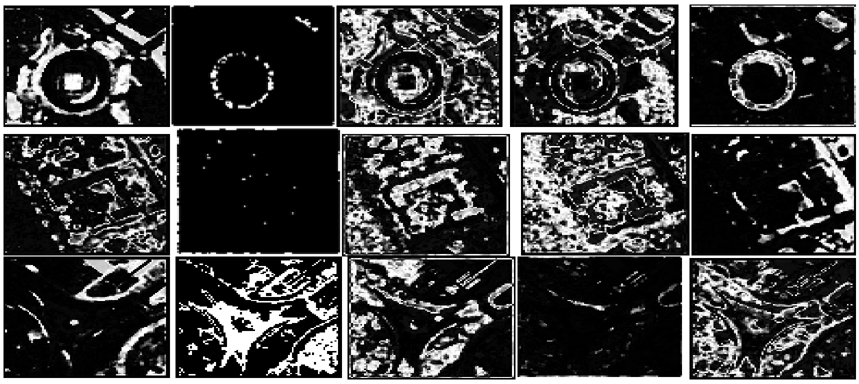
(a) (b) (c) (d)

Fig 11. (a) Input image (b) input image with speckle noise (c) gray scale image with speckle noise (d) The denoised image



(a) (b) (c) (d)

Fig 12.The segmentation result for denoised images of 11(d) when the number of cluster is four
(a) cluster one (b) Cluster two (c) cluster three (d) cluster four



(a) (b) (c) (d) (e)

Fig 13.The segmentation result for denoised images of 11(d) when the number of cluster is five
(a) Cluster one (b) Cluster two (c) cluster three (d) cluster four (e) cluster five

The segmentation result for the noisy satellite images is tabulated. From this, we can easily compare the effectiveness of the proposed approach against the various noises. The table 1 shows that the segmentation result for the input image with the Gaussian noise. Similarly, the result for the images with salt and pepper noise, Poisson noise and speckle noise is shown in the table 2, 3 and 4 respectively.

TABLE 1
Segmentation Results for the Input Image with Gaussian Noise

Sl. No	**No. of cluster**	**No. of iteration**	**Objective function**	**Execution time in seconds**
1	3	24	690.16	2.5116
2	4	30	354.49	3.4648
3	5	84	221.89	6.7704
4	6	100	150.92	9.2977

TABLE 2
Segmentation Results for the Input Image with Salt And Pepper Noise

Sl. No.	**No. of clusters**	**No. of iteration**	**Objective function**	**Execution time in seconds**
1	3	24	713.30	1.8564
2	4	41	370.21	3.1980
3	5	62	234.09	5.1324
4	6	100	159.48	9.2509

TABLE 3
Segmentation Results for the Input Image with Poisson Noise

Sl. No.	**No. of clusters**	**No. of iteration**	**Objective function**	**Execution time in sec**
1	3	22	700.23	1.4664
2	4	47	364.03	3.4788
3	5	44	227.85	5.6374
4	6	96	156.59	9.2665

TABLE 4
Segmentation Results for the Input Image with Speckle Noise

Sl No	**No. of clusters**	**No. of iteration**	**Objective function**	**Execution time in seconds**
1	3	24	674.97	2.1840
2	4	45	345.08	3.5100
3	5	65	213.16	5.9436
4	6	75	146.27	7.8781

The above results can be evaluated using six image quality measures namely Mean Square Error (MSE), Root Mean Square Error (RMSE), Signal to Noise Ratio (SNR), Peak Signal to Noise Ratio (PSNR), Average Difference (AD) and Maximum Difference (MD)

TABLE 5
Comparison of Input Image with Noisy (Gaussian) and Denoised Image using Image Quality Measures.

Parameter	**Image 2(a) &2(b)**	**Image 2(a) &2(d)**	**Image 2(b)&2(d)**
MSE	3.9233	3.7181	6.4190
RMSE	1.9807	1.9282	2.5336
SNR	9.6503e-005	-3.8622e-005	-1.3512e-004
PSNR	42.1943	42.4275	40.0561
AD	0.0011	0.0067	0.0056
MD	67	90	102

TABLE 6
Comparison of Input Image with Noisy (Salt and Pepper) and Denoised Image using Image Quality Measures.

Parameter	**Image5(a) &5(b)**	**Image5(a) &5(d)**	**Image5(b)&5(d)**
MSE	4.7215	4.4049	5.1750
RMSE	2.1729	2.0988	2.2749
SNR	5.5436e-004	-3.4089e-005	-5.8845e-004
PSNR	41.3900	41.6914	40.9917
AD	0.0036	0.0086	0.0050
MD	242	194	164

TABLE 7
Comparison of Input Image with Noisy (Poisson) and Denoised Image using Image Quality Measures

Parameter	**Image8(a) & 8(b)**	**Image 8(a) &8(d)**	**Image 8(b)&(d)**
MSE	1.7047	3.3509	4.3670
RMSE	1.3057	1.8306	2.0897
SNR	4.3377e-006	-3.7628e-005	-4.1966e-005
PSNR	45.8142	42.8792	41.7290
AD	8.0417e-004	0.0058	0.0050
MD	52	57	96

TABLE 8
Comparison of Input Image with Noisy (Speckle) and Denoised Image using Image Quality Measures.

Parameter	**Image11(a) & 11(b)**	**Image 11(a) & 11(d)**	**Image 11(b)&11(d)**
MSE	9.4689	4.6193	9.5925
RMSE	3.0772	2.1493	3.0972
SNR	3.1579e-006	-4.0165e-005	-4.3323e-005
PSNR	38.3678	41.4850	38.3115
AD	0.0071	0.0129	0.0057
MD	88	149	127

TABLE 9
Segmentation Results for Input Image with Number of Cluster is Fixed as Five

Sl No.	**Type of Noise**	**No. of iteration**	**Objective function**	**Execution time in seconds**
1	Gaussian	73	164.763	6.2754
2	Poisson	41	166.784	3.9804
3	Salt and Pepper	51	159.608	5.5537
4	Speckle	74	162.864	6.5893

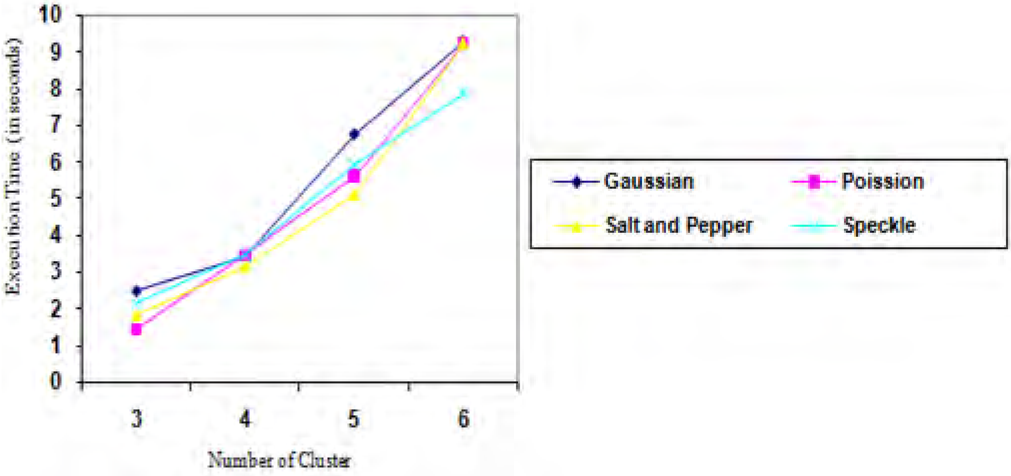


Fig 14. Computational cost (in seconds) for the various numbers of clusters with different type of noise.

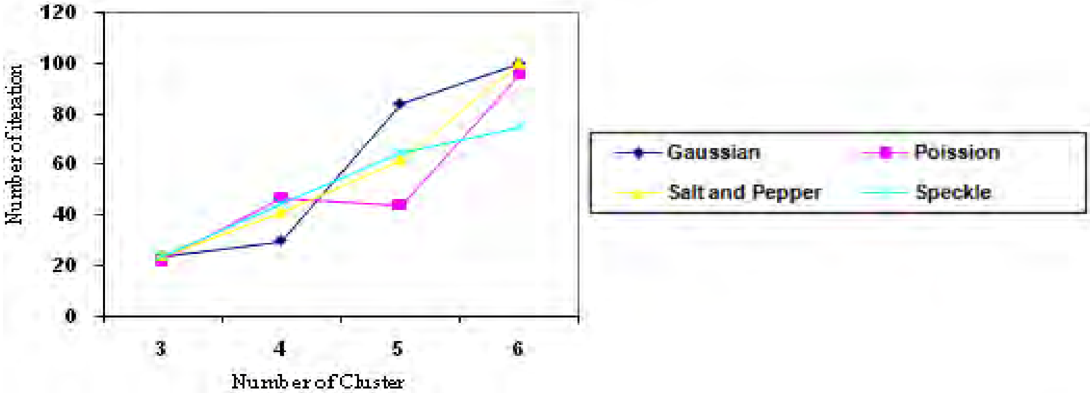


Fig 15. Number of iterations versus number of clusters for the different type of noise.

VI. CONCLUSION

This paper presents a novel method for the segmentation of noisy satellite images using Modified FCM clustering. In the standard FCM clustering algorithm, its cost or objective function never takes into account the spatial information of the image. Therefore the standard FCM clustering algorithm is very sensitive to noise and when noisy pixels are incorporated with image pixels a noisy pixel is always wrongly classified because of its abnormal feature as compared to image pixel. So in this paper, a new method has been proposed based on a new modified FCM based clustering which include the spatial information into the membership function to improve the satellite image segmentation results. Filtering of noise pixels in the image has been performed by using discrete wavelet transform and wavelet thresholding in the initial stage. Subsequently, the image is segmented for predefined number of clusters. A number of test satellite images are segmented using the proposed algorithm and the experimental results show the efficiency of the proposed approach.

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